Effect of Soil Spectral Properties on Remote Sensing of Crop Residue Cover

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Conservation tillage practices often leave appreciable amounts of crop residues on soil surfaces after harvesting and generally improve soil structure, enhance soil organic C (SOC) content, and reduce soil erosion. Remote sensing methods have shown great promise in efficiently estimating crop residue cover, and thus inferring soil tillage intensity. Furthermore, these tillage intensity estimates can be used in soil C models. Reflectance spectra of more than 4200 soils and 80 crop residues were measured in the laboratory across the 350- to 2500-nm wavelength region. Six remote sensing spectral indices were used to estimate crop residue cover: the Cellulose Absorption Index (CAI), the Lignin–Cellulose Absorption Index (LCA), the Normalized Difference Tillage Index (NDTI), the Normalized Difference Senescent Vegetation Index (NDSVI), and the Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively). Soil mineralogy and SOC affected these spectral indices for crop residue cover more than soil taxonomic order, which generally had little effect on spectral reflectance. The values of the spectral indices for soils were similar within Land Resource Regions and, specifically, for Major Land Resource Areas. The CAI showed the best separation between soils and residues, followed by LCA and NDTI. Although NDSVI, NDI5, and NDI7 had significant overlaps between soil and residue index values, assessments of crop residue cover classes may be possible with local calibrations. Future satellite sensors should include appropriate bands for assessing crop residue and nonphotosynthetic vegetation.

Abbreviations: ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; AWiFS, Advanced Wide-Field Sensor; CAI, Cellulose Absorption Index; LCA, Lignin–Cellulose Absorption Index; LRR, Land Resource Region; MLRA, Major Land Resource Region; NDI, Normalized Difference Index; NDSVI, Normalized Difference Senescent Vegetation Index; NDTI, Normalized Difference Tillage Index; NDVI, Normalized Difference Vegetation Index; SOC, soil organic carbon; SWIR, shortwave infrared; TM, Thematic Mapper.

In recent years, conservation tillage practices, including reduced-tillage and no-till methods, have become more commonplace. These methods help protect the soil from erosion, improve soil structure, and increase SOC, thus sequestering C from the atmosphere. Furthermore, recent research has shown that no-till corn is more profitable than conventional tillage systems, even with reduced yields, due to reduced labor, equipment, fuel, and irrigation costs (Archer et al., 2008; McGinnis, 2007). Paudel et al. (2006) showed that conservation tillage could be more profitable for cotton (*Gossypium hirsutum* L.) farming than conventional tillage. These profits can be further augmented by subsidies for conservation and the sale of credits for C sequestration (Causarano et al., 2006). Conservation tillage systems leave substantial quantities of crop residues on the soil surface, acting as a barrier to wind and water erosion and as a mulch, and returning nutrients to the soil, potentially reducing the need for fertilizer. Spatial information on tillage practices is also important for SOC modeling (Causarano et al., 2006, 2008). Recent economic developments can encourage farmers to use conventional tillage, however. Crude oil prices have increased the demand for biofuels, which can result in increased tillage to maximize corn grain yields or encourage the harvesting of crop residues even in reduced-tillage or no-till situations. Thus, an efficient method for measuring crop residue cover is needed.

Traditional methods of residue cover measurement, e.g., line-point transect or photographic techniques (Laflen et al., 1981), are often error prone due to operator bias, lack of contrast, and spatial variability, and are inefficient for use at the county and state levels (Morrison et al., 1993). To this end, multiple methods have been proposed utilizing remote sensing, which can rapidly map areas at minimal expense. Optically based remote sensing platforms use either space- or airborne multispectral and hyperspectral systems. Spaceborne multispectral sensors include the Landsat 4 and 5 Thematic Mapper (TM), the Indian ResourceSat 1 Advanced Wide-Field Sensor (AWiFS), and the NASA Terra Advanced Spaceborne Thermal Emission

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and Reflection Radiometer (ASTER). Airborne advanced multispectral scanners include the Moderate Resolution Imaging Spectroradiometer (MODIS) Airborne Simulator (MAS; King et al., 1996) and the MODIS/ASTER Airborne Simulator (MASTER; Hook et al., 2001). Hyperspectral sensors include the spaceborne EO-1 Hyperion (USGS, 2007) and airborne sensors, including the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS; NASA Jet Propulsion Laboratory, 2007), HYMAP (Integrated Spectronics, Castle Hill, NSW, Australia), and other commercial airborne platforms.

Optically based remote sensing methods for crop residue identification utilize a number of indices, which are tailored to specific types of sensors. These remote sensing methods fall into three basic categories: (i) normalized difference indices, (ii) spectral angle methods, and (iii) reflectance-band height indices. Normalized difference indices are commonly used with Landsat TM imagery, e.g., the NDI5 and NDI7 (McNairn and Protz, 1993), the NDTI (van Deventer et al., 1997), and the NDSVI (Qi et al., 2002). Spectral angle methods include the Crop Residue Index Multiband (Biard and Baret, 1997), which uses two or more spectral bands. Reflectance-band height indices include the CAI (Nagler et al., 2000) and LCA (Daughtry et al., 2005), which are similar in nature to hyperspectral continuum-removal methods (Clark, 1999; Clark et al., 2003a; Kokaly, 2001). Of these three methods, reflectance-band height indices usually perform the best, as they are dependent on the distinctive

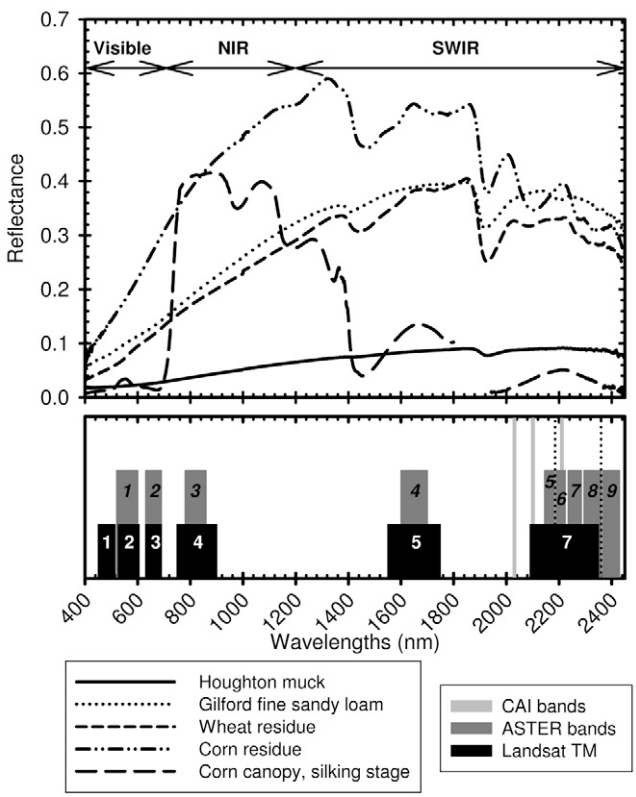

Fig. 1. Visible, near-infrared (NIR), and shortwave-infrared reflectance spectra for two soils, two crop residues, and live corn canopy, with ranges of Landsat Thematic Mapper (TM), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Cellulose Absorption Index (CAI) bands. Wheat residues were acquired from a strip-tilled field in June, ~9 mo after harvest. Corn residues were acquired from a field of standing corn residue stubble in May, ~8 mo after harvest. Corn canopy was at the silking stage (R1).

spectral features of soils and crop residues, the former of which vary depending on mineralogy, SOC, and particle size (Allen and Hajek, 1989; Clark, 1999; Daughtry et al., 2005; Kokaly et al., 2003; Schulze, 1989; Serbin et al., 2009). Because spectral angle methods do not specify which bands to use, they were not considered further in this study.

The CAI and LCA were shown to be linearly related to soils and crop residues by Daughtry et al. (2005). Soil spectral properties are a function of multiple factors, including mineralogy and composition (Baumgardner et al., 1985; Brown et al., 2006; Clark, 1999; Clark et al., 2003b; Stoner and Baumgardner, 1981; Waiser et al., 2007), water content (Daughtry and Hunt, 2008; Lobell and Asner, 2002; Nagler et al., 2000; Whiting et al., 2004), grain size (Clark, 1999; Clark et al., 2003a; Salisbury and Hunt, 1968), and structure (Ben-Dor et al., 2003). Soil minerals and compounds could bias soil CAI and LCA estimates of crop residue cover. Common soil minerals have CAI values that are around or less than zero, whereas CAI values of residues are always positive (Serbin et al., 2009). This is not always the case with LCA, however, because common soil minerals, e.g., carbonates, chlorites, and epidotes, are positively biased and can complicate these analyses (Serbin et al., 2009). Water content was also found to affect the spectral properties of soils and crop residues (Daughtry and Hunt, 2008; Serbin et al., 2008). Thus, the accuracy of remotely sensed residue estimates could be improved by incorporating soil information. Additionally, the presence of green vegetation in a pixel confounds residue cover estimation using CAI and LCA (Daughtry et al., 2005; Serbin et al., 2009).

Neither CAI nor LCA are currently practical for use from spaceborne platforms, however, because CAI can only be acquired from the EO-1 Hyperion, which is past its planned operational lifetime and suffers from bad detector lines (USGS, 2007), and ASTER is a research-only platform also past its planned operational lifetime. Thus, it is important to consider multispectral indices as an economical alternative.

Brown et al. (2006) analyzed 4193 diverse soils from within the National Soil Survey Center Soil Survey Laboratory database (Soil Survey Staff, 2007a) using a hyperspectral spectrophotometer in the laboratory to determine SOC, Fe, clay, and other contents. The aim of this study was to (i) analyze the soil spectral data from Brown et al. (2006) and other sources for spectral index value ranges, (ii) determine which indices will be effective for crop residue cover estimation based on soil orders and NRCS geographic information, i.e., Land Resource Regions (LRRs) and Major Land Resource Areas (MLRAs), and (iii) determine if existing soil survey geographic data can be used to improve remote sensing quantification of crop and residue cover.

THEORETICAL CONSIDERATIONS

Visible, Near-Infrared, and Shortwave-Infrared Spectra and Optical Sensor Bands

Remote sensing of crop residue cover traditionally utilizes visible (400–700 nm), near-infrared (700–1200 nm, NIR), and shortwave infrared (1200–2500 nm, SWIR) bands (Fig. 1). A number of spectral indices were devised for the estimation of crop residue cover utilizing the Landsat TM platform (McNairn and Protz, 1993; Qi et al., 2002; van Deventer et al., 1997). These TM indices use broad TM bands, which convolve the spectral responses across the bandwidth, and can possibly miss important spectral features that are related to crop residue or soil

mineralogy and composition (Daughtry et al., 2005; Serbin et al., 2009). Thematic Mapper indices include the NDI5 and NDI7 (McNairn and Protz, 1993), NDTI (van Deventer et al., 1997), and NDSVI (Qi et al., 2002), as well as soil-adjusted indices, e.g., the Modified Soil Adjusted Crop Residue Index (Bannari et al., 2000). Daughtry and Hunt (2008) showed that while certain soils and residues had similar spectra in the visible, NIR, and SWIR range below 1920 nm, the spectral shapes of the soils and residues were quite different in the upper-SWIR region above 1920 nm, making this spectral region ideal for residue cover estimation.

Unlike most multispectral systems, hyperspectral systems have the distinct advantage of being able to capture specific absorptions related to residues in the upper SWIR, such as the O–H bending and C–O stretching combination at 2101 nm in cellulose and other sugars (Clark, 1999; Daughtry et al., 2005; Elvidge, 1990; Kokaly and Clark, 1999; Workman and Weyer, 2008). The ASTER multispectral satellite platform is capable of imaging part of the SWIR spectrum affected by organic compounds (Daughtry et al., 2005; Workman and Weyer, 2008); however, this system misses cellulose absorption at 2101 nm.

Spectral Indices

The Landsat TM spectral indices used for this research are the NDTI (van Deventer et al., 1997):

$$\mathrm{NDTI} = \frac{\mathrm{TM5} - \mathrm{TM7}}{\mathrm{TM5} + \mathrm{TM7}} \qquad [1]$$

the NDI5 and NDI7 (McNairn and Protz, 1993):

$$\mathrm{NDI5} = \frac{\mathrm{TM4} - \mathrm{TM5}}{\mathrm{TM4} + \mathrm{TM5}} \qquad [2]$$

$$\mathrm{NDI7} = \frac{\mathrm{TM4} - \mathrm{TM7}}{\mathrm{TM4} + \mathrm{TM7}} \qquad [3]$$

and the NDSVI (Qi et al., 2002):

$$\mathrm{NDSVI} = \frac{\mathrm{TM5} - \mathrm{TM3}}{\mathrm{TM5} + \mathrm{TM3}} \qquad [4]$$

where TM3, TM4, TM5, and TM7 denote the atmospherically corrected reflectances of TM Bands 3, 4, 5, and 7, respectively (Table 1 and Fig. 1).

The reflectance-band height indices used for this research were the CAI (Nagler et al., 2000) and the LCA (Daughtry et al., 2005). The CAI is determined by

$$\mathrm{CAI} = 100\left(\frac{R_{2031} + R_{2211}}{2} - R_{2101}\right) \qquad [5]$$

where R denotes the reflectance and the subscripts 2031, 2101, and 2211 denote 11-nm-wide bands centered at 2031, 2101, and 2211 nm, respectively (Table 1 and Fig. 1). The LCA is determined as

$$\mathrm{LCA} = 100\left[2(\mathrm{A6}) - (\mathrm{A5} + \mathrm{A8})\right] \qquad [6]$$

where A5, A6, and A8 correspond to ASTER Bands 5 (2145–2185 nm), 6 (2185–2225 nm), and 8 (2295–2365 nm), respectively (Table 1 and Fig. 1). The ASTER Bands 5 and 6 fall on the slope and shoulder, respectively, of the 2101-nm cellulose absorption; ASTER Band 8 contains the C–H stretching plus CH_2 deformation combination at around 2335 nm seen in cellulose (Daughtry et al., 2005; Workman and Weyer, 2008). The CAI and LCA values that are less than −0.5 are considered to be index negative, and those that are >0.5 are considered to be index positive. Those materials whose index values reside between −0.5 and 0.5 are considered to be index neutral.

Daughtry et al. (2005) showed that residue cover estimation was most effective for pixels without significant green vegetation cover. This was confirmed for aircraft estimates of CAI by Serbin et al. (2008). High amounts of live green vegetation were also found by Gill and Phinn (2008) to confound the detection of nonphotosynthetic vegetation using LCA. An effective method of excluding green pixels is the Normalized Difference Vegetation Index (NDVI) using atmospherically corrected reflectance data from TM bands:

$$\mathrm{NDVI} = \frac{\mathrm{TM4} - \mathrm{TM3}}{\mathrm{TM4} + \mathrm{TM3}} \qquad [7]$$

Daughtry et al. (2005) suggested that pixels with green cover >0.3 be excluded from any analysis of residue cover for CAI and LCA. Serbin et al. (2008) found that NDVI ≥ 0.30 was a useful cutoff value for CAI in north-central Indiana.

Soil Mineralogy and Composition

Soils are usually heterogeneous mixtures of minerals of varying particle sizes, which can contain organic matter (Allen and Hajek, 1989; Baumgardner et al., 1985; Ben-Dor, 2002; Brown et al., 2006; Clark, 1999; Schulze, 1989; Stoner and Baumgardner, 1981). Most soil minerals are silicates, but also include oxides, hydroxides, sulfides,

Table 1. Spectral bands used for the Cellulose Absorption Index (CAI, Eq. [5]), Lignin–Cellulose Absorption Index (LCA, Eq. [6]), the Normalized Difference Vegetation Index (NDVI, Eq. [7]), Normalized Difference Senescent Vegetation Index (NDSVI, Eq. [4]), the Normalized Difference Indices 5 and 7 (NDI5 and NDI7, Eq. [2] and [3], respectively), and the Normalized Difference Tillage Index (NDTI, Eq. [1]). Some common compounds that absorb in each spectral band are listed.

Band†	Wavelengths (nm)	Index	Common absorbing compounds
R_{2031}	2026–2036	CAI	Liquid water
R_{2101}	2096–2106	CAI	Cellulose, NH_4–bearing minerals, topaz
R_{2211}	2206–2216	CAI	Clay minerals, muscovite
A5	2145–2185	LCA	Cellulose‡
A6	2185–2225	LCA	Clay minerals, muscovite
A8	2295–2365	LCA	Lignin, cellulose, calcite, dolomite, epidote, certain chlorites, vermiculite
TM3	630–690	NDVI, NDSVI	Chlorophyll
TM4	760–900	NDVI, NDI5, NDI7	Wet soil
TM5	1550–1750	NDI5, NDSVI, NDTI	Wet vegetation and soil
TM7	2080–2350	NDI7, NDTI	Wet vegetation and soil

† R_x are hyperspectral bands at the designated wavelengths; A5, A6, and A8 are Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) bands; and TM3, TM4, TM5, and TM7 are Landsat Thematic Mapper bands.

‡ Trailing edge of absorption feature.

carbonates, and others (Allen and Hajek, 1989; Schulze, 1989; Soil Survey Staff, 2007a). Texture and mineral opacity also affect soil reflectance. Reflectance will increase as grain size decreases for transparent minerals, but will decrease as grain size decreases for opaque minerals. A third class, trans-opaque, describes materials, e.g., limonite at visible wavelengths, that are transparent in one part of the spectrum and opaque in another (Baumgardner et al., 1985; Ben-Dor, 2002; Brown et al., 2006; Clark, 1999; Salisbury and Hunt, 1968).

Effect of Water Content on Soils and Crop Residues

Water content affects soil spectral properties by filling the pore spaces, creating an optically more homogeneous medium (Irons et al., 1989; Liu et al., 2002, 2003; Nagler et al., 2000, 2003; Whiting et al., 2004). This was found to affect CAI values for both soils and crop residues (Daughtry and Hunt, 2008; Nagler et al., 2000, 2003; Serbin et al., 2008). Water content had the greatest effect on the R_{2031} band, which is closest to the water absorption centered at 1930 nm (Workman and Weyer, 2008), but this was found by Serbin et al. (2008) to also be a function of SOC. Soils from Fulton County, Indiana, with low SOC showed an initial decrease in CAI with increasing water content, followed by an increase thereafter toward zero due to the way water content disproportionally affected the R_{2031} band relative to the R_{2101} and R_{2211} bands. High-SOC soils, which were measurably lower in reflectance values, had CAI values around or just below CAI = 0, regardless of water content. Crop residue CAI values were found to decrease with an increase in soil water content toward zero, showing that the contrast between soil and residue would be reduced under wet conditions (Daughtry and Hunt, 2008).

Soil Mineralogy, Texture, and Taxonomy

Soil mineralogy and texture are diagnostic for Soil Taxonomy primarily at the family and series levels (Brown, 2004; Soil Survey Staff, 2006). Mineralogy is also diagnostic for the Oxisol (<10% weatherable minerals in the fine sand fraction and low-activity clays) and Andisol (tests for poorly crystalline materials or volcanic glass) orders. While other soil orders have mineral and textural tendencies (e.g., Vertisols contain smectites and high clay content, Spodosols tend to be sandy, Ultisols tend to contain low-activity clays), however, these tendencies are either not explicitly required or not uniquely defining (smectites or high sand contents can be found in most soil orders, and not all Ultisols contain low-activity clays). While soil order might statistically predict soil texture and mineralogy, with few exceptions this level of classification does not partition soils into *distinct* texture and mineral classes.

Land Resource Regions and Major Land Resource Areas

The NRCS has three land resource categories at state and national levels for the United States (NRCS, 2006). The broadest category is the LRR. Land Resource Regions approximate broad agricultural markets comprised of geographically associated MLRAs. A Major Land Resource Area describes an area's physiography, geology, climate, hydrology, soils, biological resources, and land use. Major Land Resource Areas are then further subdivided into more specific Land Resource Units or Common Resource Areas. Land Resource Units are generally coextensive with state general soil map units, but can also be based on the subdivision of a general soil map unit when significant geographic differences in climate, water resources, or land use occur. Common Resource Areas are subdivisions of MLRAs based on a number of factors including resources, soils, hydrology, topography, and human considerations with respect to use and treatment needs. Common Resource Areas are more commonly used nationwide; Land Resource Units are widely used in the southwestern United States (NRCS, 2006).

MATERIALS AND METHODS

Acquisition of Soil and Material Spectra

Soil and material spectra used in this study were acquired from a variety of sources. The majority of the soil spectra (4193 samples) from the National Soil Survey Center Soil Survey Laboratory database (Soil Survey Staff, 2007a) utilized in this study were acquired by Brown et al. (2006) using an ASD Fieldspec Pro FR spectroradiometer (Analytical Spectral Devices, Boulder, CO) across the 350- to 2500-nm wavelength region at 1-nm intervals. In that study, soil samples were dried at 43°C for 3 d per Soil Survey Laboratory standard protocol. Samples were crushed and sieved to 2-mm diameter. Soil spectra were measured from below through borosilicate glass Petri dishes using the ASD spectroradiometer and a high-intensity-source contact probe (Analytical Spectral Devices, Boulder, CO) and calibrated against a Spectralon (Labsphere, North Sutton, NH) white reference panel. A full description of the methodology used for this data set, including selection criteria for the soils, may be seen in Brown et al. (2006). Soils were analyzed for the global set (4193 samples) and a subset of only the surface soils (893 soils with a horizon top depth of 0 cm and horizon bottom depth >0 cm).

We also acquired reflectance spectra of additional soils, crop residues, and live corn canopy with the ASD FieldSpec Pro FR spectroradiometer. Additional soil samples were acquired from Fulton County, Indiana, and measured in the laboratory. The crop residue samples consisted of 83 samples of corn (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.], wheat (*Triticum aestivum* L.), and cotton residues in the laboratory. The majority of the crop residue samples (70) were acquired in the springtime, but 13 samples of corn and soybean residues were acquired in the fall after harvest. Lab samples were illuminated by six 100-W quartz-halogen lamps mounted on the arms of a camera copy stand at 45 cm over the sample at a 45° illumination zenith angle. A current-regulated DC power supply stabilized the output of the lamps. A digital camera and the fore-optic of the spectroradiometer were aligned and positioned 90 cm from the sample surface at a 0° view zenith angle. A 1° fore-optic with a 1.6-cm-diameter field of view was used for the additional soil samples; an 18° fore-optic with a 28.5-cm-diameter field of view was used for the crop residues. The illumination and view angles were chosen to minimize shadowing and to emphasize the fundamental spectral properties of the samples. Four spectra of 100 scans each were acquired from each sample by rotating the sample tray 90° after each spectrum. All samples were placed in trays that were spray painted flat black. A 61-cm square Spectralon reference panel was placed in the field of view, illuminated, and measured in the same manner as the samples. Reflectance factors were calculated and corrected for the reflectance of the Spectralon. Because the additional soil sample spectra were acquired using a different method than used by Brown et al. (2006), the two data sets were analyzed separately. These soil samples were analyzed for total soil C by combustion at 1300°C using a LECO TruSpec CN gas analyzer (LECO Corp., St. Joseph, MI). The carbonate contents of the soils were determined using the modified pressure calcimeter method (Sherrod et al., 2002). Soil organic C was determined by subtraction of carbonate C from total C.

Reflectance spectra of green corn canopies were acquired in corn fields on 16 and 30 June and 7 and 21 July 2006 using the ASD spectroradiometer and the 18° fore-optic. The silking (R1) stage for the corn (Ritchie et al., 2005) occurred on 7 July 2006. Digital photographs were

concurrently acquired with each spectrum, and the photographs from 16 June 2006 were processed to determine the proportions of green leaves, shaded soil, and unshaded soil in the photographs.

Comparison of Spectral Indices

Basic statistical parameters (mean, median, standard deviation, and range) were computed for index values of the soils from Brown et al. (2006), the crop residues, and the live corn canopy. The spectral index data for each distinct group (soils, residues, and live corn) were compared to assess potential relationships between pairs of indices using Pearson correlation and descriptive statistics. Specifically, we calculated Pearson correlation coefficients (r) and sample population sizes (n) for all three groups. The critical $|r|$ values at a 95% confidence interval (P value) of normal distribution were calculated from Student's t-test values as (Chatterjee and Price, 1977)

$$|r| = \frac{t}{\sqrt{(n-2)+t^2}} \qquad [8]$$

where t values were determined from Lide (2008). Index sensitivity to live vegetation and crop residue cover were determined by comparison of r values to NDVI and CAI, respectively.

Soil Reflectance as a Function of Soil Order and Land Resource Unit

The soil spectra acquired by Brown et al. (2006) were matched against pedon and layer information from the National Soil Survey Center Soil Survey Laboratory database (Soil Survey Staff, 2007a). For the majority of samples, data such as horizon type, top and bottom depths, soil taxonomy, geographic coordinates, LRR and MLRA, mineralogy, and other parameters were available. While LRR and MLRA were available in the National Soil Survey Center Soil Survey Laboratory database, entries were not as extensive as were geographic coordinates for soil samples, so these data were specifically queried using vector geographic information system data provided by the NRCS (2006) in conjunction with the geographic coordinates from the database (Soil Survey Staff, 2007a). Soils from LRRs outside the conterminous United States, i.e., Alaska, Hawaii, Puerto Rico, the U.S. Virgin Islands, and the Pacific Basin, were not included in the LRR analysis.

RESULTS

Spectral Properties of Soils, Residues, and Live Vegetation

Soil and crop residue spectra can be similar, as shown in Fig. 1. In this figure, the spectra of two Fulton County, Indiana, soils and two crop residues are displayed alongside a live corn canopy spectrum.

The corn canopy spectrum shows major differences from both soils and both crop residues in reflectance values and spectral shape across all wavelengths. The Gilford series soil (a coarse-loamy, mixed, superactive, mesic Typic Endoaquoll) and crop residues in this figure had spectral similarities for wavelengths shorter than the water absorption band at 1930 nm (Workman and Weyer, 2008). This was particularly the case for degraded wheat residues (9 mo in the field and lying flat on the ground) and the Gilford soil sample, which appear to be very similar. One soil sample of the Houghton series (euic, mesic Typic Haplosaprist), however, was significantly darker than the other soils and residues due to higher SOC, and spectrally featureless except for the water absorption at 1930 nm. For wavelengths >1930 nm, crop residues showed evidence of the O–H bending and C–O stretching combination absorption centered at 2101 nm (Daughtry, 2001; Workman and Weyer, 2008).

As crop residue degrades, the reflectance values decrease across all wavelengths and the relative depth of the O–H bending and C–O stretching combination absorption centered at 2101 nm decreases. Fall residues (~1 mo in the field) had mean CAI values of 5.8 and 5.4 for corn (eight samples) and soybean (five samples), respectively. For these fall residues, CAI ranged from 4.3 to 7.1 for corn and from 4.3 to 6.6 for soybean. For springtime residues (~7–9 mo in field), corn (39 samples) and soybean (26 samples) values ranged from CAI = 1.1 to 6.3 and 1.4 to 4.6, respectively, with mean values at 2.9 for both types of crop residue.

Different spectral shapes in the SWIR spectrum affect CAI and LCA bands, as seen in Fig. 2. For CAI, concavity in reflectance values renders CAI-positive values, such as the corn residue (~7 mo in the field, but with standing corn residue stubble 30–45-cm high) with CAI = 6.3 and degraded wheat residue (~9 mo in the field) at CAI = 1.1. The discrepancy between the corn and soybean CAI values is largely due to residue piece size; small-

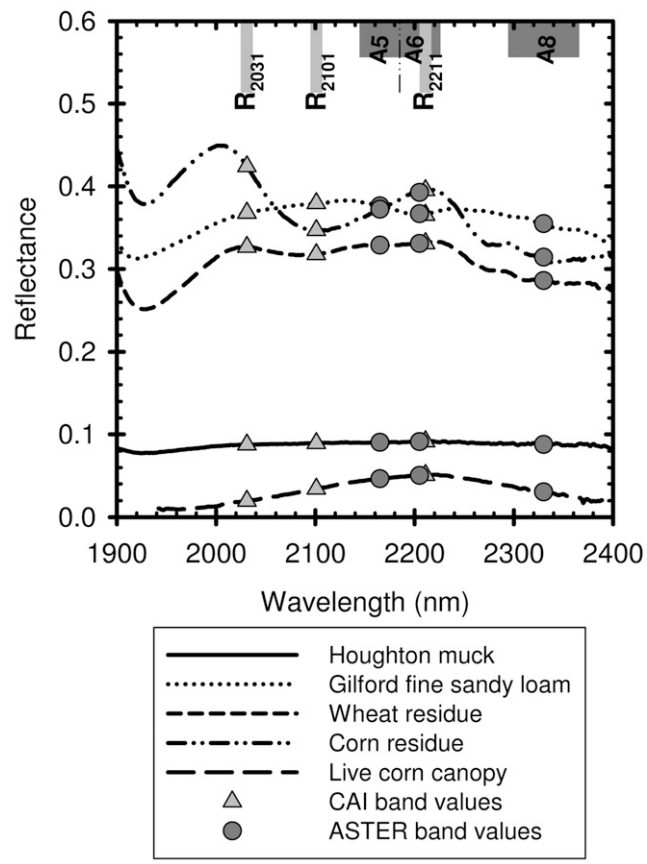

Fig. 2. Shortwave-infrared reflectance (*R*) spectra for two soils, two crop residues, and live corn canopy. Wheat residues were acquired from a strip-tilled field in June, ~9 mo after harvest. Corn residues were acquired from a field of standing corn residue stubble in May, ~8 mo after harvest. Corn canopy was at the silking stage (R1). Gray triangles and dark gray circles denote Cellulose Absorption Index (CAI) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) band values, respectively. Gray and dark gray columns at the top of the chart denote widths of CAI and ASTER bands, respectively; A5, A6, and A8 denote ASTER Bands 5, 6, and 8, respectively.

er residues degrade faster, whereas large residues such as corn can survive for more than a year in the field. In fact, multiple soybean residue samples contained the previous year's corn residue in them. Additionally, residues that contain standing stubble will degrade more slowly because they are less in contact with soil microorganisms and soil water (Steiner et al., 1999), as can be seen with the corn sample in Fig. 2. Spectral convexity in CAI bands will produce CAI-negative values, as seen for the Gilford series soil, with CAI = −1.3. Spectra that show linear change produce CAI-neutral values, e.g., the green corn canopy and Houghton series soils produced values of 0.1 and 0.0, respectively. With ASTER bands, spectral concavity produces LCA-negative values, and convexity LCA-positive values (the opposite behavior to CAI). Hence, in Fig. 2 the clean corn residue, degraded wheat residue, and green corn canopy produced LCA = 9.9, 4.7, and 2.4, respectively; the Gilford and Houghton series soils are LCA neutral at 0.2 and 0.4, respectively. In many soils, mineral-OH absorptions affect R_{2211} and ASTER Band 6, which can render them index-negative. This absorption feature, albeit small, was enough to render the Gilford series soil in Fig. 2 CAI-negative; however, it was not large enough to affect LCA.

Spectral Index Values of Soils, Crop Residues, and Live Corn Canopy

Comparison of Spectral Indices

Spectral index mean values, medians, standard deviations, and ranges of soils, crop residues, and live corn canopy are shown in Table 2 to assess the discrimination potential of pixel components from one another. For all indices, the surface soils subset showed decreased ranges compared with the full data set. The decrease in ranges also included a decrease in standard deviations for most indices. Mean and median values also varied between the surface soils subset and the entire soils data set due to the narrower range of soil properties in the surface horizons.

Median values (which were similar to mean values), along with 10th, 25th, 75th, and 90th percentile data plus outliers of CAI, LCA, NDTI, NDSVI, NDI5, and NDI7 values for soil orders showed shifts between the global soils spectral data set and the surface soils subset in Fig. 3 and 4, respectively. Median values of CAI were lower for the global soil data set (Fig. 3) than for the surface soils data set (Fig. 4). The LCA generally showed an increase in median value for the surface soils subset (Fig. 4) compared with the global set (Fig. 3). Median values of NDTI decreased from the global soils data set (Fig. 3) to the surface soils data set (Fig. 4). The NDSVI showed general increases and NDI5 and NDI7 showed decreases in median values for the surface soils subset (Fig. 4) compared with the global soils data set (Fig. 3). The shift in values is related in large part to mineralogy, whereby deeper layers contain more clays or carbonates, which have distinctive spectral features affecting indices (Allen and Hajek, 1989; Brown et al., 2006; Clark, 1999; Clark et al., 2003b; Dixon, 1989; Serbin et al., 2009). Of all of these indices, CAI contrasts the best between soils and crop residues. In general, exposure of subsurface strata is likely to increase the contrast between crop residue and soil for CAI. The opposite case, however, can be true with respect to the other indices, which show overlapping values for both the global and surface soils data sets. For these other indices, noticeable overlaps between soil and crop residue index values exist for surface soils, which increase for the global soils data set. As such, many of these indices, which may be useable over uneroded landscapes, may not be appropriate in adjacent eroded areas.

Soil spectral index data correlations to one another may be seen in Table 3 for the global soil data set. For this population, all of the normalized difference indices (NDVI, NDSVI, NDI5, and NDI7) correlated with one another except NDTI. The CAI correlated best with NDTI ($r = -0.80$), such that a soil with a relatively high CAI value was likely to have a low NDTI value and vice versa. The LCA was found to correlate less with NDTI than CAI. While it is difficult to assess exactly why the correlation between CAI and NDTI is better than the correlation between CAI and LCA, it should be noted that ASTER Band 8 contains a number of mineral absorptions that do not affect the CAI (Serbin et al., 2009), which may account for the lower $|r|$.

Table 2. Statistics for the spectral indices Normalized Difference Vegetation Index (NSVI), Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) for all soil samples and the surface soils subset from Brown et al. (2006), crop residues, and live corn canopy.

Material		NDVI	CAI	LCA	NDTI	NDSVI	NDI5	NDI7
All soils $n = 4193$	mean	0.12	−3.5	−2.5	0.03	0.27	−0.15	−0.12
	median	0.11	−3.4	−2.5	0.02	0.24	−0.14	−0.11
	SD	0.05	1.6	1.6	0.04	0.13	0.10	0.11
	range	−0.01 ∼ 0.43	−10.5 ∼ −0.1	−12.4 ∼ 8.3	−0.13 ∼ 0.25	−0.20 ∼ 0.73	−0.57 ∼ 0.20	−0.59 ∼ 0.30
Surface soils $n = 854$	mean	0.16	−2.5	−1.9	0.00	0.35	−0.21	−0.21
	median	0.15	−2.5	−2.1	0.00	0.35	−0.20	−0.20
	SD	0.05	0.9	1.2	0.03	0.12	0.10	0.10
	range	0.02 ∼ 0.38	−9.8 ∼ −0.3	−5.6 ∼ 3.9	−0.10 ∼ 0.16	0.00 ∼ 0.71	−0.57 ∼ 0.07	−0.59 ∼ 0.10
Crop residues $n = 83$	mean	0.19	3.3	7.0	0.14	0.40	−0.22	−0.09
	median	0.19	3.0	6.9	0.14	0.40	−0.22	−0.10
	SD	0.02	0.9	1.3	0.04	0.07	0.07	0.10
	range	0.15 ∼ 0.27	1.1 ∼ 7.1	3.3 ∼ 11.5	0.02 ∼ 0.22	0.23 ∼ 0.53	−0.36 ∼ −0.07	−0.33 ∼ 0.10
Green corn canopy $n = 40$	mean	0.77	0.0	3.0	0.36	0.64	0.32	0.58
	median	0.85	0.0	2.8	0.43	0.68	0.39	0.70
	SD	0.16	0.2	0.6	0.13	0.11	0.16	0.23
	range	0.42 ∼ 0.93	−0.4 ∼ 0.3	2.15 ∼ 4.65	0.12 ∼ 0.50	0.41 ∼ 0.77	0.01 ∼ 0.54	0.14 ∼ 0.82

Crop residue spectral index correlations may be seen in Table 4. The NDVI did not correlate well with any index for this data set. The CAI and LCA agreed the best with each other in comparison with other indices. The NDTI correlated better with LCA than CAI. For TM-based indices, NDSVI, NDI5, and NDI7 all correlated very well with each other. Most indices were positively correlated with CAI. These positive correlations were related to residue quality, with the freshest (least degraded) residues having the highest values, and decreasing as the residue sample quality degraded. The NDSVI, however, showed an inverse relationship with CAI and varying behavior between spring and fall residues. The highest spring NDSVI values were for degraded residues, whereas better quality residues showed lower NDSVI values. Crop residue NDSVI had a logarithmic coefficient of determination with CAI of $r^2 = 0.54$. Fall crop residues, however, showed no consistent relationship between CAI and NDSVI, with a linear coefficient of determination of $r^2 = 0.07$.

The live corn canopy (Table 5) showed excellent correlations for all normalized difference indices (NDVI, NDTI, NDSVI, NDI5, and NDI7) with one another, and wide ranges of index values, as can be seen in Fig. 3 to 5. The CAI showed agreement with all indices (Table 5), but had a very narrow range of green vegetation values clustered around CAI = 0, particularly in comparison with CAI values of soils and residues (Fig. 3–5).

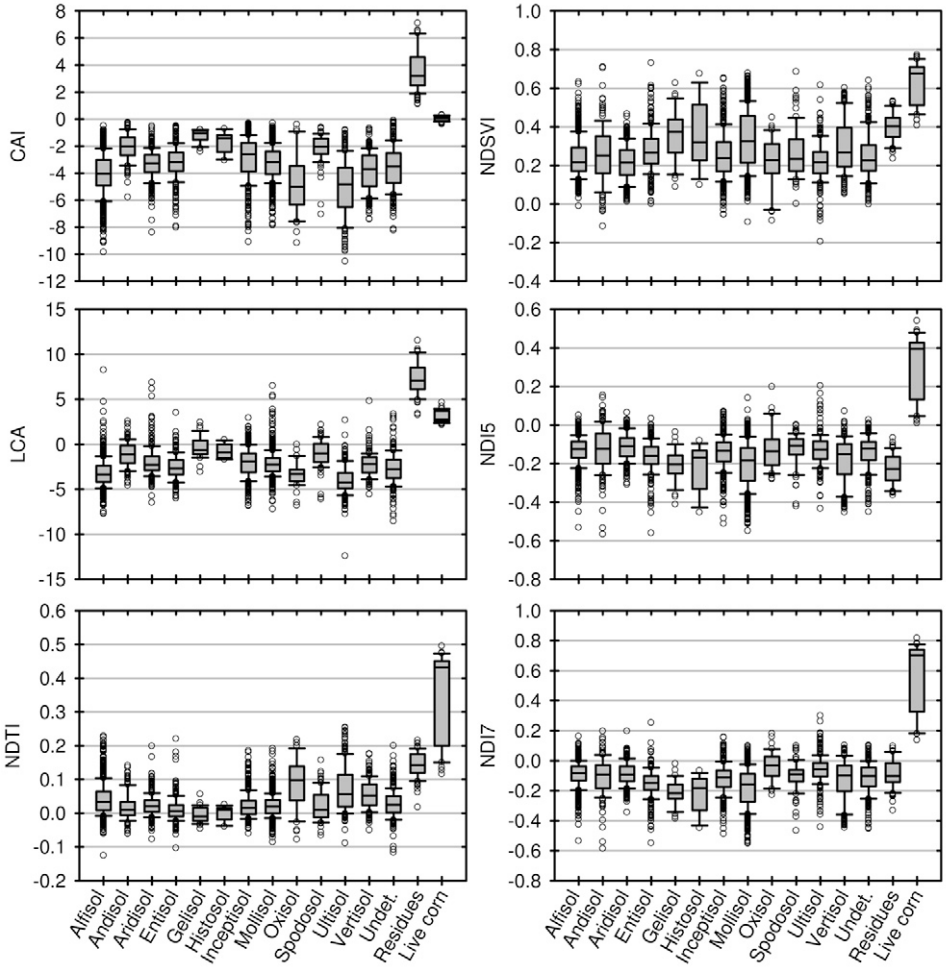

Fig. 3. Ranges of Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) values for all soil sample spectra from Brown et al. (2006), as grouped by soil taxonomic order. Top and bottom whiskers denote 90th and 10th percentiles, respectively, and the tops and bottoms of the boxes denote the 75th and 25th percentiles, respectively. The lines inside the boxes denote median values. Circles denote outlier values beneath and above the 10th and 90th percentiles, respectively. Undet. denotes undetermined taxonomy.

Soil Taxonomy and Crop Residue Spectral Indices

Of the 4193 soil samples that were analyzed, 324 of these were not assigned to a taxonomic order by the National Soil Survey Center Soil Survey Laboratory (Soil Survey Staff, 2007a). Crop residue indices for these soils, alongside crop residues and corn canopy, are shown in Fig. 3. Additionally, we have displayed index values for surface soil samples (854 samples, 74 of which had undetermined taxonomy) in Fig. 4. We did not assess whether or not any of these surface soil samples were acquired from eroded soil profiles.

All soils in Fig. 3 were CAI-negative in value, while all crop residues were always CAI-positive. Green corn canopy had CAI values around zero. The ranges of soil CAI regardless of depth are similar for several orders, with a few exceptions. Gelisols and Histosols had the fewest samples but had the highest median and 75th percentile CAI values of all of the soils groups, as well as the smallest ranges (Fig. 3). While this may be attributable to small sample sizes, it is more likely due to the preponderance of organic materials that occur in these taxonomic orders, which would reduce the range of CAI values (Serbin et al., 2009; Soil Survey Staff, 2006). Ultisols had the widest range of CAI values, whereas Gelisols showed the smallest range. The lowest median and 25th percentile values were in Oxisols and Ultisols.

The LCA values of soil varied from LCA-negative to LCA-positive (Fig. 3). This was expected, as a number of common soil minerals had similar or greater values than did crop residues (Serbin et al., 2009). Two of the soil orders sampled, Gelisols and Spodosols, had at least 25% of the populations that equaled or exceeded LCA = 0. The soil sample with the highest LCA value, an R horizon (unweathered bedrock layer) underlying an Indiana Alfisol loess of the Ryker series (fine-silty, mixed, active, mesic Typic Paleudalf), had LCA = 8.3 as it is composed of calcite, which was shown to be strongly LCA-positive (Serbin et al., 2009). The lowest LCA value soil (LCA = −12.4) was for a Shinbone series CR horizon (fine-loamy, siliceous, active, mesic Typic Hapludult) Ultisol horizon from North Carolina that contained kaolinite, which can bias LCA negatively, and mica. The

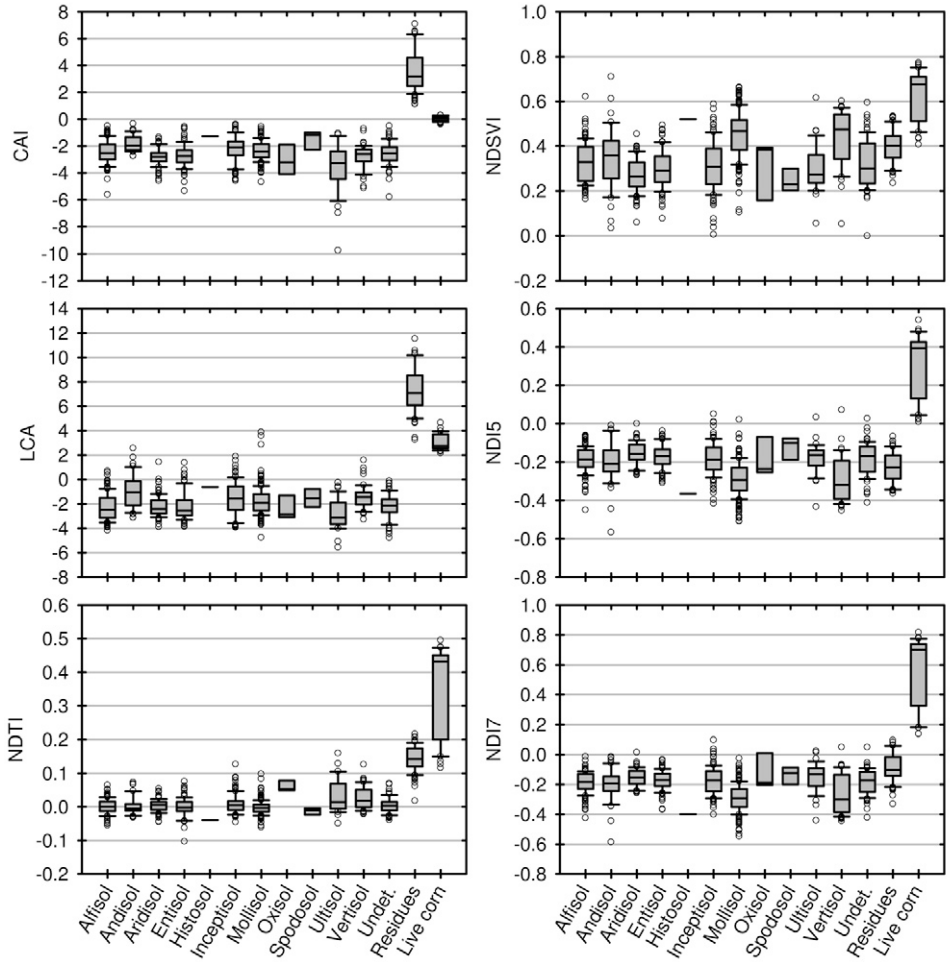

Fig. 4. Ranges of Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) values for surface soil sample spectra from Brown et al. (2006), as grouped by soil taxonomic order. Top and bottom whiskers denote 90th and 10th percentiles, respectively, and the tops and bottoms of the boxes denote the 75th and 25th percentiles, respectively. The lines inside the boxes denote median values. Circles denote outlier values beneath and above the 10th and 90th percentiles, respectively. Undet. denotes undetermined taxonomy.

specific species of mica was not determined by the Soil Survey Laboratory (Soil Survey Staff, 2007a); depending on the specific mica mineral species, the LCA may vary from strongly positive to strongly negative values (Serbin et al., 2009). While the CAI and LCA ranges of these soil orders do vary, the absolute ranges of these values when coupled with outlier values (those under the 10th and over the 90th percentile) show measureable overlap. These overlaps also appear to be duplicated across small spatial distances: spectral data from Fulton County, Indiana, shows that soil spectral properties were similar for Alfisols, Entisols, Inceptisols, and Mollisols, with only Histosols being discernable due to their high SOC (Fig. 6). Furthermore, the Fulton County soils have similar mineralogy (Serbin et al., 2008). As such, taxonomic-order-based spectral index calibrations for these indices would be impractical. There was also a small overlap in LCA values between degraded residues and corn canopy. Due to this overlap and the tendency of green canopy to shade and obscure residues and soils, green pixels should be excluded from analyses using NDVI or a similar vegetation index as in Daughtry et al. (2005).

The surface soil sample subset showed decreased ranges of CAI and LCA values (Fig. 4) compared with the global soil sample set (Fig. 3). There still exist some very index-negative soils, however, such as the Clifton series (fine, mixed, semiactive, mesic Typic Hapludult) Ap horizon from North Carolina that contained kaolinite and had a CAI value of −9.8. The highest CAI value (−0.3) belonged to an Andisol of the Manu series (ashy, amorphic, isothermic Aquic Hapludand) A horizon from Hawaii, which contained mostly glasses with some plant opal and diatoms; this soil also had a total indiscriminate C content of 18.21% (Soil Survey Staff, 2007a), which darkened the soil and caused the CAI values to be close to zero (Serbin et al., 2009). The maximum LCA value (3.9) was a Mollisol sampled as the Takpochao series (clayey-skeletal, mixed, active, isohyperthermic Lithic Haplustoll) A1 horizon from the Northern Mariana Islands that contained significant amounts of calcite and plant roots (Soil Survey Staff, 2007a), both of which can positively bias LCA (Serbin et al., 2009). In Fig. 4, the CAI and LCA ranges overlap for the orders, thus soil order is not a good indicator of what values of CAI or LCA would apply to a given soil series.

Table 3. Correlation coefficients (*r*) for the spectral indices Normalized Difference Vegetation Index (NDVI), Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) for all soils (critical $|r|$ at $P \geq 0.95$ is 0.03, n = 4193 samples).

Index	NDVI	CAI	LCA	NDTI	NDSVI	NDI5	NDI7
NDVI	1.00						
CAI	0.27	1.00					
LCA	0.26	0.64	1.00				
NDTI	−0.15	−0.80	−0.34	1.00			
NDSVI	0.88	0.13	0.19	−0.12	1.00		
NDI5	−0.72	−0.05	−0.14	0.10	−0.96	1.00	
NDI7	−0.69	−0.37	−0.26	0.49	−0.89	0.92	1.00

The NDTI performed the best of the TM-based indices; the other three indices (NDSVI, NDI5, and NDI7) did not achieve good results. These indices separated best between soils and live green corn canopy, usually due to water absorption features affecting TM Bands 5 and 7 (Hunt and Rock, 1989). Live green corn canopy was found to overlap the ranges of soils and residues, however, particularly at early growth stages, such that a vegetation index such as NDVI should be used to separate out green pixels beforehand to minimize noise be-

fore analysis, as per Daughtry et al. (2005). The NDTI showed some separability between residues and all soil samples, albeit that there was a potentially problematic overlap with Oxisols and Ultisols, both of which had similar 90th percentile values to residues. These values were reduced when compared only with surface soil samples (Fig. 4), for which overlaps were limited to the 90th percentile Ultisol and 10th percentile residue values, and some outlier values of soils and degraded residues. A number of soils that had overlapping values with crop residues contained either kaolinite or montmorillonite, both of which are strongly CAI-negative minerals and are discussed in depth below. In general, it appears that NDTI may be usable in many areas, particularly when crop residues are in good condition and the soils are relatively uneroded. The NDSVI appeared to separate poorly among all surface samples excepting Spodosols and showed a fair amount of overlap with Aridisols, on which the index was originally developed (Qi et al., 2002). Furthermore, the NDSVI also showed overlap between green corn canopy and residues and soils. Both NDI5 and NDI7 show unacceptable overlaps for residues and soils in Fig. 4.

Land Resource Regions, Major Land Resource Areas, and Crop Residue Spectral Indices

Surface soils from the 48 conterminous United States were analyzed by index and grouped by LRR in Fig. 5 and Table 6. As expected, the ranges of index values were generally less when sorted by LRR than by soil order for surface samples. There were three reasons for this: (i) there were more categories in which to bin the data, (ii) there were fewer data points (since a number of surface soil samples were acquired from outside the 48 conterminous United States), and (iii) LRRs represent spatially contiguous areas with similar physical and climatological features, which result in similar soils, and thus, spectral properties.

The CAI values for most LRRs showed that the 10th and 90th percentile values were usually within 2 CAI value points of each other (Fig. 5). Certain LRRs located in the southern and eastern United States showed higher standard deviations than other LRRs for CAI values in Table 6, namely LRRs J (Southwestern Prairies Cotton and Forage Region, extending from Kansas to Texas), N (East and Central Farming and Forest Region, extending from Oklahoma to Pennsylvania and New York), P (South Atlantic and Gulf Slope Cash Crops, Forest, and Livestock Region, extending from Texas and Oklahoma to Virginia), and T (Atlantic and Gulf Coast Lowland Forest and Crop Region, extending from Texas to New Jersey). Land Resource Region N, which showed the largest standard deviation, included the Clifton series Ultisol (CAI = −9.8), albeit that this soil CAI value was significantly less than the other soils in this LRR. The Clifton series soil was found to share the same MLRA (130B, Blue Ridge) as three other soils, which included the soil with the highest CAI value for this LRR, the Balsam series (loamy-skeletal, isotic, frigid Humic Dystrudept). The Balsam series soil was sampled twice by Brown et al. (2006) and had CAI values of −0.4 and −0.5, and contained 14.68 and 10.33% gravimetric SOC as determined by the National Soil Survey Center Soil Survey Laboratory (Soil Survey Staff, 2007a). Both Balsam series samples contained small x-ray diffractometry peaks for kaolinite, vermiculite, and mica in the <0.002-mm fraction (Soil Survey Staff, 2007a) but CAI values close to zero because of the high organic matter content. The Clifton series sample, however, contained less organic matter (5.49% SOC) and visible mica flakes; x-ray diffractometry of the <0.002-mm fraction had stronger kaolinite and vermiculite peaks than the Balsam series, and also showed the presence of goethite (Soil Survey Staff, 2007a). All four soil samples in this MLRA were from two neighboring counties (Mitchell and Yancey) in North Carolina. The other two soils in this MLRA were the Dellwood series (sandy-skeletal, mixed, mesic Oxyaquic Dystrudept) with CAI = −1.1 and the Thunder series (loamy-skeletal, mixed, active, mesic Humic Hapludult) with CAI = −2.5. Of these four soils, the Clifton and Balsam series samples were from Mitchell County; Dellwood and Thunder series were from Yancey County. While these two counties had a diverse range of CAI values, they also have limited agricultural activity, as they are mountainous. The Clifton series occurs in a limited number of counties in the Appalachian Mountains of northern Georgia, Tennessee, and North Carolina, and in two counties in northern Virginia, with one county in Georgia reporting 13.6% areal coverage. The Balsam series is restricted to adjacent counties of North Carolina and Tennessee, and one county in southwestern Virginia, with the highest county areal extent being 2.1%. The Dellwood series is limited to several adjacent counties in the Appalachian Mountains of North Carolina and Tennessee and one county in southwestern Virginia, and in all cases areal extents were 1.1% or less. The Thunder series is limited to three adjacent counties in North Carolina and one county in southwestern Virginia and ranged from 0.4 to 8.1% areal extents in these counties. Other MLRAs in this LRR had CAI value ranges

Table 4. Correlation coefficients (*r*) for the spectral indices Normalized Difference Vegetation Index (NDVI), Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) for crop residues (critical $|r|$ at $P \geq 0.95$ is 0.22, n = 83 samples).

Index	NDVI	CAI	LCA	NDTI	NDSVI	NDI5	NDI7
NDVI	1.00						
CAI	−0.40	1.00					
LCA	−0.32	0.93	1.00				
NDTI	−0.29	0.60	0.71	1.00			
NDSVI	0.45	−0.37	−0.32	−0.34	1.00		
NDI5	−0.22	0.30	0.26	0.29	−0.97	1.00	
NDI7	−0.30	0.48	0.48	0.62	−0.92	0.93	1.00

Table 5. Correlation coefficients (*r*) for the spectral indices Normalized Difference Vegetation Index (NDVI), Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) for live corn canopy (critical $|r|$ at $P \geq 0.95$ is 0.31, n = 40 samples).

Index	NDVI	CAI	LCA	NDTI	NDSVI	NDI5	NDI7
NDVI	1.00						
CAI	0.81	1.00					
LCA	0.34	0.74	1.00				
NDTI	0.98	0.87	0.42	1.00			
NDSVI	0.99	0.75	0.23	0.96	1.00		
NDI5	0.99	0.82	0.34	0.99	0.98	1.00	
NDI7	0.99	0.85	0.39	1.00	0.97	0.99	1.00

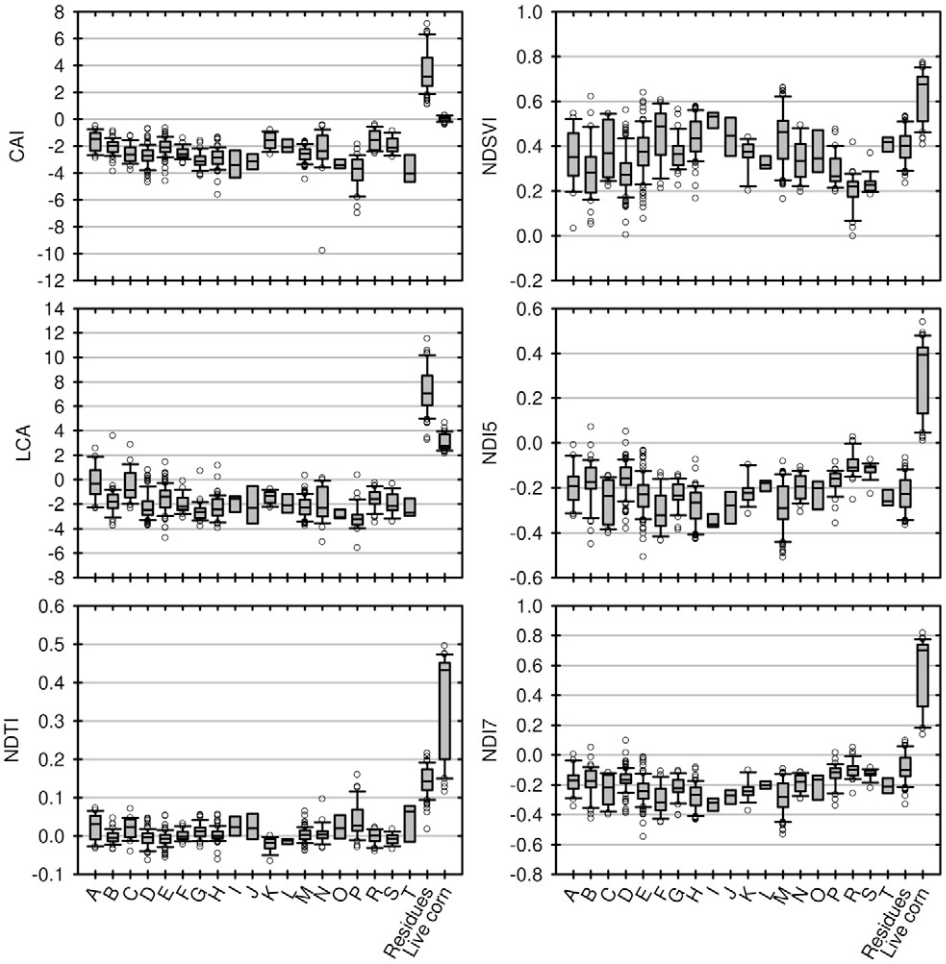

Fig. 5. Ranges of Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) values for surface soil sample spectra from Brown et al. (2006), as grouped by Land Resource Region (LRR, uppercase letters on *x* axis, Table 6). Mean values and standard deviations are shown in Table 6. Top and bottom whiskers denote 90th and 10th percentiles, respectively, and the tops and bottoms of the boxes denote the 75th and 25th percentiles, respectively. The lines inside the boxes denote median values. Circles denote outlier values beneath and above the 10th and 90th percentiles, respectively.

that were significantly less, e.g., MLRA 118 (Arkansas Valley and Ridges) with CAI values ranging from −3.0 to −3.5, or MLRA 120 (Kentucky and Indiana Sandstone and Shale Hills and Valleys) with CAI values ranging from −1.5 to −3.6 (in each case four soil samples from each MLRA were sampled).

The LCA values showed an overall decreasing trend for maximal values from the western conterminous United States toward the eastern United States. In some cases this is due to the dry climates found in most of the western states, which allows a number of minerals that are unstable in wetter climates, such as calcite, to exist in the soil (Doner and Lynn, 1989). The soil with the highest LCA value (LCA = 3.6, Fig. 5) was from the Thosand series in Custer County, Idaho, a fine-loamy, mixed, superactive, calcareous Calcic Cryaquoll, in LRR B (Northwestern Wheat and Range Region in Washington, Oregon, Idaho, and Utah). Wet climates such as the Pacific Northwest, however, can also harbor LCA-positive soils. The highest LCA value soil in LRR A (Northwestern Forest, Forage, and Specialty Crop Region) was a Litchy series soil sample (medial-skeletal, ferrihydritic Oxyaquic Duricryand). This soil contained some minerals identified by Serbin et al. (2009) as LCA-positive, e.g., vermiculite and goethite, or potentially LCA-positive (pyroxene, undifferentiated into individual mineral species in Soil Survey Staff, 2007a). However, the Litchy series, which is found in the Olympic National Forest in the state of Washington, is of very limited areal extent (<0.3%) there. Unlike other western LRRs, LRR A, which extends from California to Washington, has some of the highest amounts of rainfall in the conterminous United States. In LRR C (California Subtropical Fruit, Truck, and Specialty Crop Region), the soil with the highest LCA value belonged to the Hentine series, a loamy-skeletal, magnesic, thermic Lithic Argixeroll from Stanislaus, CA, which contained a large amount of antigorite, a strongly LCA-positive serpentine mineral (Serbin et al., 2009). The Hentine series was restricted to four counties in California and was of very limited areal extent (the highest county value was 0.7%). Soils from LRRs A and C also had the highest median LCA values, whereas LRR B was more or less in line with other LRRs elsewhere in the country. Western LRRs (A–E) all had large standard deviations (≥1.0). As with the CAI, LRRs J, N, and P also had large standard deviations of LCA values. Land Resource Region P contained the lowest LCA value soil, which was the Rion series sample (fine-loamy, mixed, semiactive, thermic Typic Hapludult) from North Carolina (LCA = −5.6). Ranges of LCA values varied less within specific MLRAs than in their LRR, e.g., MLRA 134 (Southern Mississippi Valley Silty Uplands) LCA values ranged from −3.9 to −2.9, MLRA 133B (Western Coastal Plain) values ranged from −3.2 to 0.4, and MLRA 136 (Southern Piedmont, which contained the Rion series soil) varied from −5.6 to −2.8, whereas for the whole of LRR P these values ranged from −5.6 to 0.4. The Rion series extends from Alabama to Virginia, with the maximal areal extent being 10.2% for a county in North Carolina.

The NDTI values for most soils and undegraded crop residues generally were separable, except for some overlap for LRRs N and P. In these LRRs, a number of soils had NDTI values in excess of the 10th percentile for crop residues (NDTI = 0.09). In LRR N, the Clifton series sample had an NDTI value of 0.10. In LRR P, three soil series from two MLRAs had NDTI values exceeding the 10th percentile values of residues. From MLRA 135 (Alabama, Mississippi, and Arkansas Blackland Prairie) in Marengo County, Alabama, the Vaiden series (very-fine, smectitic, thermic Aquic Dystrudert) had NDTI = 0.13. The Vaiden

series extends from southeastern Texas to Alabama, with one county in Mississippi containing up to 13.2% areal extent. In MLRA 136 (Southern Piedmont), three soils had high NDTI values, namely an unnamed clayey, kaolinitic, thermic Typic Kanhapludult originally identified as being with the Cecil series from Oconee County, Georgia, with NDTI ranging from 0.06 to 0.13 (five samples from the same location), the Hiwassee series (fine, kaolinitic, thermic Rhodic Kanhapludult from Rowan County, North Carolina) with values ranging from 0.11 to 0.16 (two samples from the same location), and the Rion series (one sample), which had an NDTI value of 0.09. With the exception of the Vaiden series, which was smectitic, all the other soils with NDTI values ≥0.09 contained significant quantities of kaolinite as determined by the National Soil Survey Center Soil Survey Laboratory (Soil Survey Staff, 2007a). Of these soils, the Cecil series is the most prevalent geographically according to the NRCS Soil Extent Mapping Tool (Soil Survey Staff, 2007b). The Cecil series extends from Alabama to Virginia, and in several counties in Georgia and South Carolina areal extents exceed 50%. The Hiwassee series extends from Alabama to northern Virginia with up to 19.1% county areal extents occurring. Soils that had high NDTI values in this LRR also had low CAI values (between CAI = −4.4 and −7.0, considering the inverse correlation between CAI and NDTI), showing that while NDTI would be difficult for use with those soils, CAI would have increased contrasts in this region. This also suggests that NDTI may be problematic in areas where clayey horizons (kaolinitic, montmorillonitic, etc.) may be present at the surface. Separability between residues and soils appeared to be best for LRRs K (Northern Lake States Forest and Forage Region, from Minnesota to Michigan), L (Lake States Fruit, Truck, and Dairy Region, from Illinois to New York), R (Northeastern Forage and Forest Region, from Ohio to Maine), and S (Northern Atlantic Slope Diversified Farming Region, extending from West Virginia and Virginia to New York and Massachusetts).

The NDSVI showed much overlap between soils and residues for most LRRs, with the exception of LRRs R and S (both of which are located in the northeastern United States), which showed separation of values between 10th percentile residue (NDSVI = 0.30) and 90th percentile soil values. Two outlier soils for these LRRs are the Amostown series (coarse-loamy, mixed, active, mesic Oxyaquic Dystrudept, NDSVI = 0.42) of Plymouth County, Massachusetts, in MLRA 144A (New England and Eastern New York Upland, Southern Part) of LRR R, and the Glenelg series (fine-loamy, mixed, semiactive, mesic Typic Hapludult, NDSVI = 0.37) of Frederick County, Maryland, in MLRA 148 (Northern Piedmont) of LRR S. The Amostown series is of very limited geographic extent and only found in Massachusetts, with the highest county areal extent being 2.5% and the remainder being <0.3%. The Glenelg series, on the other hand, extends from Virginia through Maryland and northern Delaware to southeastern Pennsylvania, with some counties in Maryland and Pennsylvania having areal extents between 10 and 33% (Soil Survey Staff, 2007b). Due to the inverse relationship between residue quality and NDSVI, the best separation between fresh, clean crop residue and soil was for LRR I (Southwest Plateaus and Plains Range and Cotton Region, in Texas). The NDSVI did show some contrast for median values of residues (NDSVI = 0.40) and soils (NDSVI = 0.27) of LRR D (Western Range and Irrigated Region, extending from Texas to Wyoming, Oregon, and California), within which Qi et al. (2002) developed that index; that said, a good deal of overlap between crop residue and soils value ranges of that LRR existed, and the three soils from MLRA 41 (Southeastern Arizona Basin and Range) sampled by Brown et al. (2006) ranged from NDSVI = 0.29 to 0.37, within the range of clean spring crop residues.

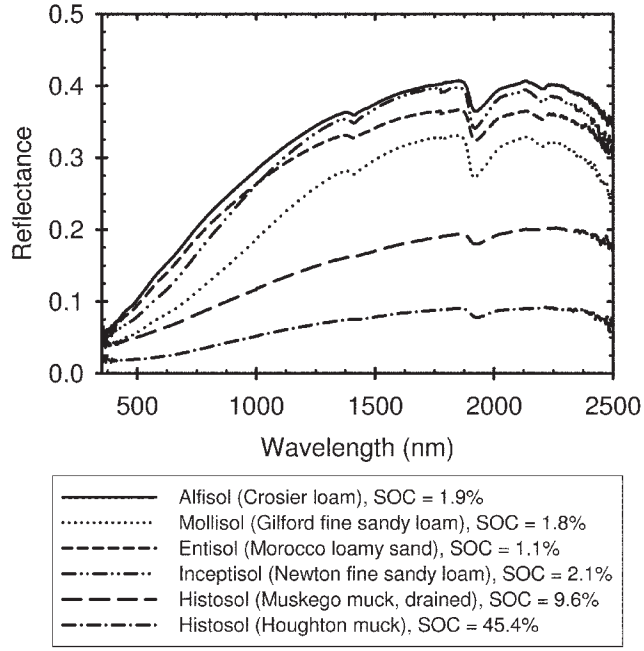

Fig. 6. Spectra of six soil samples acquired from Fulton County, Indiana, with varying soil organic C (SOC) content. Soil orders were determined from SSURGO maps and NRCS Official Soil Series Descriptions (Soil Survey Staff, 2007b).

The NDI5 only appeared to have reasonable separability for LRR I, albeit that the small number of spectra makes evaluation of this index difficult. Some limited use of NDI5 may be possible for degraded residues in LRRs R and S.

The NDI7 fared better than the NDI5 for separability of values between residues and soils; however, it lacked the contrast that was seen with NDTI. It may work best in LRRs I and J with relatively fresh residues.

Soils and the Normalized Difference Vegetation Index

Soil spectra from Brown et al. (2006) were used to calculate the NDVI, with results in Table 2. The majority of corn canopy spectra had NDVI values (median NDVI = 0.85) well in excess of those from both soils and residues. The lowest corn canopy NDVI was for early stage corn (from 16 June 2006) when the mean green cover and sunlit soil areas from the corn canopy spectra were 40.7 and 35.4%, respectively. Maturation of the corn canopy minimized the sunlit soil areas, and thus the effect of soil on scene NDVI. In all cases, the median NDVI values of soils and crop residues were <0.20. Crop residues had a very limited range of NDVI values and were very distinct from those of green vegetation (Table 2). Certain soil samples had NDVI values >0.40, but these soils occurred seldom in the conterminous United States.

The ranges of NDVI values for surface horizon samples were reduced and median values were shifted in comparison with the global soils data set (Table 2). The few surface soils with NDVI > 0.3 included the Takpochao series from Rota, Northern Mariana Islands; the Maho Bay series (loamy, mixed, superactive, isohyperthermic, shallow Typic Haplustoll) from St. John, U.S. Virgin Islands; the Merriman series (medial-skeletal, ferrihydritic Pachic Fulvicryand) from Clallam County, Washington; and the Litchy series from Grays Harbor, Washington. The Merriman series soil is from the Olympic National Forest and of very limited areal extent (0.2% of the national forest area).

For most soils, an NDVI value of 0.30 should be sufficient for separation of green vegetation pixels from bare soil pixels. Local calibration of soil spectral properties is advised, however, for determining the appropriate NDVI value for the separation of green vegetation pixels from bare soil and residue pixels.

Table 6. Statistical means and standard deviations for the Cellulose Absorption Index (CAI), Lignin–Cellulose Absorption Index (LCA), Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), and Normalized Difference Indices 5 and 7 (NDI5 and NDI7, respectively) for 688 surface soils by Land Resource Region (LRR) for the 48 conterminous United States in the National Soil Survey Center Soil Survey Laboratory database (Soil Survey Staff, 2007a,b), 83 crop residues, and 40 live corn spectra shown in Fig. 5.

LRR code or material	LRR name	CAI	LCA	NDTI	NDSVI	NDI5	NDI7	*n*
A	Northwestern Forest, Forage, and Specialty Crop	−1.6 ± 0.7	−0.1 ± 1.4	0.02 ± 0.03	0.36 ± 0.12	−0.19 ± 0.08	−0.17 ± 0.09	21
B	Northwestern Wheat and Range	−2.0 ± 0.6	−1.8 ± 1.1	0.00 ± 0.02	0.29 ± 0.13	−0.18 ± 0.10	−0.18 ± 0.10	48
C	California Subtropical Fruit, Truck, and Specialty Crop	−2.6 ± 0.7	−0.5 ± 1.3	0.02 ± 0.03	0.38 ± 0.12	−0.26 ± 0.09	−0.24 ± 0.10	24
D	Western Range and Irrigated	−2.7 ± 0.7	−2.2 ± 1.0	−0.01 ± 0.02	0.28 ± 0.09	−0.16 ± 0.07	−0.17 ± 0.07	108
E	Rocky Mountain Range and Forest Region	−2.1 ± 0.7	−1.6 ± 1.1	−0.01 ± 0.02	0.37 ± 0.11	−0.23 ± 0.09	−0.24 ± 0.09	95
F	Northern Great Plains Spring Wheat	−2.5 ± 0.4	−2.0 ± 0.7	0.00 ± 0.01	0.46 ± 0.12	−0.30 ± 0.09	−0.30 ± 0.10	27
G	Western Great Plains Range and Irrigated	−3.1 ± 0.6	−2.6 ± 0.8	0.01 ± 0.02	0.37 ± 0.07	−0.23 ± 0.06	−0.22 ± 0.07	35
H	Central Great Plains Winter Wheat and Range	−2.9 ± 0.7	−2.3 ± 0.9	0.00 ± 0.02	0.43 ± 0.09	−0.28 ± 0.08	−0.27 ± 0.09	63
I	Southwest Plateaus and Plains Range and Cotton	−3.3 ± 0.9	−1.9 ± 0.7	0.03 ± 0.03	0.52 ± 0.04	−0.35 ± 0.03	−0.33 ± 0.05	8
J	Southwestern Prairies Cotton and Forage	−3.4 ± 1.1	−2.1 ± 1.6	0.02 ± 0.03	0.44 ± 0.10	−0.28 ± 0.08	−0.26 ± 0.08	8
K	Northern Lake States Forest and Forage	−1.6 ± 0.6	−1.4 ± 0.5	−0.02 ± 0.02	0.36 ± 0.06	−0.22 ± 0.06	−0.24 ± 0.06	17
L	Lake States Fruit, Truck Crop, and Dairy	−2.0 ± 0.5	−2.0 ± 0.8	−0.01 ± 0.01	0.33 ± 0.03	−0.19 ± 0.02	−0.20 ± 0.03	6
M	Central Feed Grains and Livestock	−2.6 ± 0.5	−2.2 ± 0.8	0.00 ± 0.02	0.44 ± 0.12	−0.28 ± 0.10	−0.28 ± 0.11	98
N	East and Central Farming and Forest	−2.5 ± 1.8	−2.0 ± 1.4	0.01 ± 0.03	0.34 ± 0.09	−0.19 ± 0.06	−0.19 ± 0.06	24
O	Mississippi Delta Cotton and Feed Grains	−3.3 ± 0.3	−2.9 ± 0.4	0.02 ± 0.03	0.37 ± 0.10	−0.22 ± 0.07	−0.20 ± 0.09	4
P	South Atlantic and Gulf Slope Cash Crops, Forest, and Livestock	−3.9 ± 1.2	−3.1 ± 1.0	0.04 ± 0.05	0.30 ± 0.07	−0.17 ± 0.05	−0.13 ± 0.07	44
R	Northeastern Forage and Forest	−1.6 ± 0.7	−1.6 ± 0.8	0.00 ± 0.02	0.21 ± 0.08	−0.10 ± 0.06	−0.10 ± 0.06	34
S	Northern Atlantic Slope Diversified Farming	−1.9 ± 0.6	−2.0 ± 0.8	−0.01 ± 0.01	0.23 ± 0.04	−0.12 ± 0.03	−0.13 ± 0.03	18
T	Atlantic and Gulf Coast Lowland Forest and Crop	−3.7 ± 1.2	−2.4 ± 0.7	0.04 ± 0.05	0.40 ± 0.06	−0.24 ± 0.05	−0.20 ± 0.08	6
Residue		3.3 ± 0.9	7.0 ± 1.3	0.14 ± 0.04	0.40 ± 0.07	−0.22 ± 0.07	−0.09 ± 0.10	83
Live corn		0.0 ± 0.2	3.0 ± 0.6	0.36 ± 0.13	0.64 ± 0.11	0.32 ± 0.16	0.58 ± 0.23	40

CONCLUSIONS

Soil order did not have a consistent effect on soil spectral index values. Soils were more spectrally similar within LRRs and specifically MLRAs, albeit that certain MLRAs had wide ranges of diversity with respect to spectral index values. Soil spectral properties, and thus index values, were affected primarily by soil mineralogy and SOC content. The ranges of surface horizon soil index values were less than those of the global data set, which included soil index values from all horizons.

The best index to use was CAI, which showed complete separation between soils and residues, followed by LCA and NDTI, which generally separated soils and residues well, with a few notable exceptions. The CAI and NDTI were inversely correlated with good agreement. Soils with high carbonate contents or with minerals that are strongly LCA-positive had similar LCA values to crop residues. These LCA-positive soils occur primarily in western LRRs of the 48 conterminous United States. Soils containing appreciable amounts of clay minerals (e.g., kaolinite and montmorillonite) decreased the differences between soil and residue for NDTI, but increased the contrast for CAI. These soils occur primarily in the southeastern United States (LRR P), but could also occur elsewhere when subsurface horizons become exposed by erosion.

Although NDSVI, NDI5, and NDI7 values for soils and crop residues frequently overlapped, sufficient contrasts for successful classification may exist in some areas. For example, NDSVI could be a useful index in LRR R of the northeastern United States if certain outlier soils are not prevalent in the scene.

In all cases, green pixels should be excluded from the analysis via NDVI or a similar vegetation index. Green pixel removal is of particular concern for the TM-based residue cover indices, which can be overly biased by any green vegetation in the pixel. Daughtry et al. (2005) recommended that pixels with NDVI > 0.3 be masked out to eliminate the effects of vegeta-

tion on residue cover estimation, as canopy effectively obscures residue and soil.

We suggest that local ground truth reflectance spectra of crop residues and soils be acquired and analyzed to determine which indices and sensors are appropriate. Although sensors such as Systeme Pour l'Observation de la Terre (SPOT) and AWiFS do not have the optimum bands in the SWIR wavelength region required for the CAI, LCA, and NDTI indices, assessments of crop residue cover classes may be possible with local spectrophotometric calibrations. Spectrophotometric calibrations should cover the range of soils in a scene and should include reflectance measurements of the soils for several water contents from air dry to water saturated to allow more accurate results under dynamic field conditions. These local calibrations of soil and crop residue spectral properties can, in conjunction with soil and crop residue water content spatial information, improve crop residue cover estimation accuracy for most indices by providing endpoints for 0 and 100% crop residue cover situations.

Future hyperspectral and advanced multispectral sensors should include CAI bands for crop residue and nonphotosynthetic vegetation detection. Additionally, researchers should consider the use of CAI for monitoring grass- and rangelands. We feel that CAI should be useful not only for monitoring tillage practices and subsequent C sequestration modeling, but also for rangeland applications and fire risk hazards.

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